EXHIBIT 430

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On the Use of the Multivariate Regression Model in Event Studies

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1. *Introduction*

A Multivariate Regression Model (*MVRM*) methodology to measure the effect of new information on asset prices was first suggested in Gibbons [1980, appendix H]. In this paper I outline the use of that methodology to measure abnormal returns and to test hypotheses about these returns. Included are advantages of the *MVRM* methodology over other event study methodologies and some of its problems in hypothesis testing.[1]

Section 2 discusses the *MVRM* technique relative to better-known methodologies. In section 3 I compare these methodologies and argue that the primary advantage of the *MVRM* is in testing joint hypotheses. Section 4 provides small sample evidence on several test statistics used in the *MVRM*; section 5 summarizes the paper.

2. *Event Studies in the MVRM*

Since the original paper by Fama et al. (FFJR) [1969] a number of researchers have used their so-called event study methodology to examine the effect of new information on asset prices. FFJR estimate the market

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[1] While writing this paper I became aware of a paper by Schipper and Thompson [1985] which, in reference to their 1983 article, makes some of the points discussed here.

model:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \tilde{u}_{it} \tag{1}$$

for the stock of firm i with data including the time period containing the event of interest. Abnormal returns for the sample firms are measured as the residuals from (1) during the event period and the residuals are then cross-sectionally averaged (in event time). The hypothesis that the average abnormal return equals zero is tested, using a cross-sectional estimate of the standard deviation of the residuals.

The FFJR approach assumes that the residuals are independent and identically distributed. There are three problems with this assumption. First, the abnormal returns—i.e., the expectations of the residuals—are likely to differ across firms. Second, there is evidence that the residual variance differs across firms (see Fama [1976, pp. 129–39]). Finally, the residuals will not be independent if the event occurs during the same calendar time period for some firms and these firms are in the same or related industries. The dependence is especially severe when both of these conditions exist for all the sample firms.

Several recent event studies have used the *MVRM* when the event occurs during the same calendar period for every firm to overcome the above statistical problems. Binder [1983], Schipper and Thompson [1983], Hughes and Ricks [1984*a*], Madeo and Pincus [1984], and Pownall [1984] represent examples of this approach. The basic methodology was first proposed by Gibbons [1980, appendix H].

The *MVRM* methodology begins by parameterizing the abnormal returns γ_{ia} in the individual return equations:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \sum_{a=1}^{A} \gamma_{ia} D_{at} + \tilde{u}_{it}, \tag{2}$$

using dummy variables D_{at}. If there are A announcements about the event, each D_{at} equals one during the period of the ath announcement and zero otherwise.[2] When the explanatory variables in the return-generating process are the same for each of the N stocks the system of return equations:

$$\begin{aligned}
\tilde{R}_{1t} &= \alpha_1 + \beta_1 \tilde{R}_{mt} + \sum_{a=1}^{A} \gamma_{1a} D_{at} + \tilde{u}_{1t} \\
\tilde{R}_{2t} &= \alpha_2 + \beta_2 \tilde{R}_{mt} + \sum_{a=1}^{A} \gamma_{2a} D_{at} + \tilde{u}_{2t} \\
&\vdots \\
\tilde{R}_{Nt} &= \alpha_N + \beta_N \tilde{R}_{mt} + \sum_{a=1}^{A} \gamma_{Na} D_{at} + \tilde{u}_{Nt},
\end{aligned} \tag{3}$$

[2] Alternatively, only one dummy variable, which equals one every period there is an announcement, could be used. In this case, gamma measures the average abnormal return during the announcement periods.

can be estimated jointly as a *MVRM*.[3]

This approach allows the individual abnormal returns (gammas) to differ across firms. One assumption is that the disturbances are independent and identically distributed within each equation, but their variances differ across equations. It is also assumed that across equations (firms), the contemporaneous covariances of the disturbances $E(\tilde{u}_{it}\tilde{u}_{jt})$ are nonzero, whereas the noncontemporaneous covariances $E(\tilde{u}_{it}\tilde{u}_{j,t-k})$ all equal zero. Because of the assumed structure of the variance-covariance matrix of the disturbances, the *MVRM* requires that the observations in each equation are from the same calendar time period.[4]

3. *The Advantages of the MVRM Methodology*

The *MVRM* estimates the individual return equations jointly with generalized least squares, but the estimated coefficients and standard errors are identical to the estimates obtained from ordinary least squares estimation of the individual equations (see Theil [1971, chap. 7]). Therefore, there are no gains in efficiency from using the *MVRM* approach to estimate the parameters of (3). The advantages of the approach are in hypothesis testing since heteroscedasticity across equations and contemporaneous dependence of the disturbances are explicitly incorporated into the hypothesis tests. This avoids the statistical problems in the FFJR methodology.

While a number of different hypotheses about the excess returns can be tested, the three hypotheses in table 1 seem to be of primary interest in this literature.[5] Tests of $H1$ are similar to those conducted by FFJR. $H2$ and $H3$ are joint hypotheses that the abnormal returns equal zero either for all firms and all announcements, or for all firms and a given announcement. Tests of $H2$ and $H3$ will be more powerful tests of whether an event affects the sample firms than tests of $H1$ when the abnormal returns differ in sign. The joint hypothesis tests are of special importance when the *MVRM* methodology is applied to regulatory events since there is good reason to believe that regulation benefits some firms and hurts others.[6]

Although tests of $H1$ in the *MVRM* are well specified, there are

[3] The return equations could also express the returns net of the riskless rate, as in Schipper and Thompson [1983], or include other explanatory variables, e.g., dummies for beta shifts and intercept shifts, either in January or over the subperiod from the first to the last announcement, as in Binder [1983].

[4] Theil [1971, chap. 7] discusses the *MVRM* in the context of the more general Seemingly Unrelated Regression Model.

[5] Other hypotheses are listed in table 2 of Binder [1983].

[6] Regulatory events are more likely to be studied because the announcements often occur on the same date (e.g., Senate passage of a law) for all relevant firms, so the *MVRM* requirement that the observations in each equation are from the same calendar time period can be met without deleting firms from the sample. Evidence on asymmetric effects of regulation is discussed in Binder [1983, pp. 6-7].

TABLE 1
Hypotheses of Primary Interest in MVRM Event Studies

Hypothesis	Description
$H1$: $\frac{1}{N}\sum_i \gamma_{ia} = 0$	The average abnormal return during announcement period a equals zero.
$H2$: $\gamma_{ia} = 0 \ \forall\ i, a$	All abnormal returns equal zero.
$H3$: $\gamma_{io} = 0 \ \forall\ i$	All normal returns for announcement period a equal zero.

alternatives to test this hypothesis that are both correctly specified and econometrically and computationally simpler. For example, Izan [1978] forms an equally weighted portfolio of stocks of banks affected by mandatory audit regulation and estimates the portfolio return equation:

$$\tilde{R}_{pt} = \alpha_p + \beta_p \tilde{R}_{mt} + \sum_{a=1}^{A} \gamma_{pa} D_{at} + \hat{u}_{pt}. \tag{4}$$

The estimated average abnormal return $\hat{\gamma}_{pa}$ in (4) is equal to the arithmetic average of the $\hat{\gamma}_{ia}$'s in (3). In fact, Hughes and Ricks [1984*b*] have shown that the t^2 test of the hypothesis that γ_{pa} equals zero is equivalent to an F test (see section 4) in the *MVRM* of $H1$.[7] Hence, the major advantage of the *MVRM* methodology is in testing joint hypotheses since $H1$ can be tested in the portfolio framework of (4).[8]

4. *Testing Joint Hypotheses in the MVRM*

Although there are a number of statistics available to test joint hypotheses in the *MVRM*, the distributions of many of these statistics are known only asymptotically. In this section I discuss a statistic whose small sample distribution is generally known to a highly accurate approximation and in some cases is exactly known, and four statistics with well-known asymptotic distributions. Evidence indicates that the asymptotic statistics are biased in tests with as many as 60 monthly returns or 250 daily returns.

The statistic whose distribution is known to an accurate approximation is discussed in Rao [1951; 1973]. He expands the distribution function of a likelihood ratio statistic and expresses it as a series of terms involving the beta distribution. An F-distributed statistic is derived using only the first term of the expansion, since the remaining terms are of order $0(T^{-4})$ or smaller, where T is the sample size. This approximation is very accurate, given that the tests in the *MVRM* generally use at least 60 observations (in the case of monthly data). In fact, when N, the number

[7] Hughes and Ricks also show that the statistic used in the F test, which is generally asymptotically F distributed, is exactly F distributed in this case.

[8] Similarly, if abnormal returns are measured as market model residuals or prediction errors, hypothesis tests about the average abnormal return which use the "portfolio method" introduced by Jaffe [1974] and Mandelker [1974] are well specified.

of equations in the system, or q, the number of restrictions tested per equation, is less than or equal to two the test statistic is exactly F distributed (see Rao [1973, p. 555]).

The best-known test statistics applied in this context are the Wald and F statistics. Zellner [1962] uses the Wald test in his seminal paper on the Seemingly Unrelated Regression Model (*SURM*). Theil [1971, p. 314] discusses the F statistic and it is reported by the SAS computer package for hypothesis tests in the *SURM*.[9] When the variance–covariance matrix of the disturbances in the *MVRM* is known, these statistics are distributed as chi-squared (for the Wald) and F. In practice, the true variance–covariance matrix is replaced by a consistent estimate and the statistics are asymptotically (with respect to T) chi-squared and F.[10] Schipper and Thompson [1983] use the Wald test and Binder [1981] uses the F test.

However, Laitinen [1978] and Meisner [n.d.] find that the Wald test is biased against the null hypothesis in small samples, based on the asymptotic distribution. They simulate a system of demand equations, constrained by the null hypothesis, and estimate the Wald statistic 100 times. The frequency of the rejection of the null increases monotonically with the number of equations. For example, Meisner rejects the null at the 5% level 9 times in 100 with five equations, but 96 times in 100 with fourteen equations! Although Laitinen and Meisner do not simulate the F statistic using an estimated variance–covariance matrix, we can infer from their results that the F statistic will also reject the null too often since it is proportional to the Wald statistic.[11]

Two other tests in this literature are based on the Lagrange Multiplier (LM) and the Likelihood Ratio (LR) statistics. These statistics are also asymptotically chi-squared distributed, and exactly chi-squared when the variance–covariance matrix is known.[12] Berndt and Savin [1977] demonstrate that the following inequality:

$$LM \leq LR \tag{5}$$

holds between these statistics in the *MVRM*.[13] Since they have the same

[9] Theil also discusses the Wald test. See the SAS Institute [1979] on PROC SYSREG.

[10] See Theil [1971, p. 403].

[11] Meisner [n.d., pp. 3–4] shows that the F statistic equals the Wald statistic divided by Q, the total number of restrictions tested. Since the F statistic is proportional to the Wald, and the Wald rejects too often (is too large) when the variance–covariance matrix is estimated, the F statistic must also reject too often (be too large) when calculated with the estimated covariance matrix.

[12] See Berndt and Savin [1977] and Buse [1982].

[13] Berndt and Savin [1977] show that when the Wald statistic is calculated using T as the divisor in the estimated variance–covariance matrix of the disturbances, expression (5) becomes $LM < LR \leq$ Wald. I use the degrees of freedom per equation, $T - K$, as the divisor since the statistic is calculated this way by Schipper and Thompson [1983]. The value of the Wald statistic would increase if T were used.

asymptotic distribution, the *LM* test rejects less often than the *LR* test, based on critical values from the chi-squared distribution.

Although Laitinen [1978] and Meisner [n.d.] show that the Wald and *F* tests are biased in their applications with 31 time-series observations, it is of interest to investigate the extent to which they will be biased in tests with stock return data and the larger sample sizes common in *MVRM* event studies. Evidence on the small sample behavior of the *LR* and *LM* tests would also be useful. Binder [1983] provides evidence on the sample properties of these statistics in a *MVRM* study of 20 regulatory changes enacted from 1887 to 1978 using stock market data. Sixty months of returns are used to estimate the system and $H2$ is tested first with Rao's *F* test, and then with the four asymptotic tests discussed above.

Table 2 reports the five test statistics and the associated p-values for the 20 regulatory changes. The number of equations N, the number of announcement months A, and the length of the event period, which equals the number of months from the first announcement to the last announcement (inclusive), are also shown. Rao's *F* test, reported in the first column, rejects $H2$ once at the 5% level and three times at the 10% level. Figure 1 shows the rejection rate by Rao's *F* test in table 2 for tests of different size. For example, if the size of the test is .10, the null hypothesis $H2$ is rejected in 3 of 20 cases. A 45-degree line, indicated by dots, is included for reference. The *F*, Wald, *LR*, and *LM* statistics and their p-values are shown in the remaining columns of table 2. $H2$ is rejected 9 times in 20 at the 5% level and 10 times in 20 at the 10% level with the *F* test. The rejection rate for the Wald test is identical; in fact, the difference in the p-values for the *F* and Wald statistics is generally less than .01. The *LR* statistic also rejects the null hypothesis nine times at the 5% level and ten times at the 10% level. The *LM* test is more conservative (see expression (5)), rejecting twice and four times at the 5 and 10% levels.

The frequency of rejection of $H2$ by each statistic is illustrated in figures 2 through 5. Each figure shows the rejection rate of $H2$ for tests of different sizes. The bias in these tests can be inferred by comparing their rejection rates to the rejection rates for Rao's *F* test in figure 1. Figures 2 and 3 indicate that the *F* and Wald tests are highly biased against the null hypothesis since they yield more frequent rejections than Rao's *F* test. These results parallel those of Laitinen [1978] and Meisner [n.d.] since the bias increases with the number of equations. For example, the p-values of the *F* and Wald statistics are close to those of Rao's *F* test when the number of equations is small, as per the regulations in 1934, 1935, 1938, and 1975, but are much lower than the p-values of Rao's *F* when N is large. When there are 21 equations (the Water Quality Act of 1965) the *F* and Wald tests reject at the .0004 and .0002 levels, while Rao's *F* does not reject even at the .50 level!

TABLE 2

Tests with Monthly Returns of the Hypothesis H2 That All Excess Returns Equal Zero

Regulatory Change	Year	N	A	Event Period	Rao's F Test Statistic	Rao's F Test p	F Test Statistic	F Test p	Wald Test Statistic	Wald Test p	LR Test Statistic	LR Test p	LM Test Statistic	LM Test p
Interstate Commerce Act	1887	9	4	39	F(36,147.9) = .51	.9891	F(36,423) = .64	.9518	χ^2 (36) = 22.87	.9562	χ^2 (36) = 26.54	.8750	χ^2 (36) = 24.27	.9317
Public Utility Regulation	1907	5	6	23	F(30,166) = 1.42*	.0856	F(30,225) = 1.65**	.0221	χ^2 (30) = 49.59**	.0137	χ^2 (30) = 54.92**	.0036	χ^2 (30) = 46.44**	.0282
Communications Act	1934	2	7	24	F(14,94) = .25[a]	.9971	F(14,96) = .26	.9967	χ^2 (14) = 3.62	.9974	χ^2 (14) = 4.43	.9923	χ^2 (14) = 4.34	.9930
Banking Act	1935	2	5	7	F(10,96) = .84[a]	.5932	F(10,98) = .89	.5476	χ^2 (10) = 8.88	.5439	χ^2 (10) = 10.05	.4361	χ^2 (10) = 9.30	.5039
Civil Aeronautics Act	1938	2	4	6	F(8,104) = .62[a]	.7635	F(8,106) = .63	.7495	χ^2 (8) = 5.05	.7518	χ^2 (8) = 5.55	.6975	χ^2 (8) = 5.38	.7163
Natural Gas Field Price Regulation	1954	8	8	47	F(64,237.2) = .75	.9176	F(64,376) = .93	.6360	χ^2 (64) = 59.32	.6424	χ^2 (64) = 63.46	.4956	χ^2 (64) = 54.30	.8010
Drug Amendments	1962	8	4	38	F(32,163.9) = 1.30	.1452	F(32,408) = 1.56**	.0283	χ^2 (32) = 50.05**	.0221	χ^2 (32) = 50.20**	.0213	χ^2 (32) = 43.33*	.0872
Water Quality Act	1965	21	4	10	F(84,124.9) = 1.00	.5020	F(84,1071) = 1.64**	.0004	χ^2 (84) = 138.09**	.0002	χ^2 (84) = 121.56**	.0046	χ^2 (84) = 93.82	.2174
Interest Rate Control Act	1966	3	2	3	F(6,104) = 2.33**[a]	.0375	F(6,162) = 2.42**	.0286	χ^2 (6) = 14.54**	.0241	χ^2 (6) = 15.14**	.0192	χ^2 (6) = 14.21**	.0274
National Traffic and Motor Vehicle Safety Act	1966	5	4	21	F(20,156.8) = 1.52*	.0803	F(20,255) = 1.97**	.0092	χ^2 (20) = 39.33**	.0061	χ^2 (20) = 35.32**	.0185	χ^2 (20) = 27.72	.1162
Coal Mine Health and Safety Act	1969	3	5	16	F(15,132.9) = .74	.7419	F(15,50) = .79	.6828	χ^2 (15) = 11.92	.6851	χ^2 (15) = 13.27	.5815	χ^2 (15) = 12.35	.6524
Rail Passenger Service Act	1970	14	6	24	F(84,207) = 1.16	.2039	F(84,686) = 1.66**	.0004	χ^2 (84) = 139.12**	.0001	χ^2 (84) = 128.68**	.0012	χ^2 (84) = 101.20*	.0974
Clean Air Act Amendments	1970	5	5	13	F(25,168.7) = 1.18	.2642	F(25,245) = 1.32	.1443	χ^2 (25) = 33.11	.1284	χ^2 (25) = 35.92*	.0728	χ^2 (25) = 32.07	.1560
Federal Water Pollution Control Act Amendments	1972	16	4	10	F(64,143.2) = 1.05	.3948	F(64,816) = 1.49**	.0093	χ^2 (64) = 95.43**	.0006	χ^2 (64) = 90.53**	.0162	χ^2 (64) = 74.32	.1774
Bank and S & L Deregulation	1973	14	1	1	F(14,43) = 1.55[a]	.1359	F(14,784) = 2.01**	.0147	χ^2 (14) = 28.18**	.0135	χ^2 (14) = 24.46**	.0403	χ^2 (14) = 20.08	.1276
Brokerage Deregulation	1975	2	7	19	F(14,98) = .76[a]	.7062	F(14,100) = .78	.6899	χ^2 (14) = 11.12	.6760	χ^2 (14) = 12.41	.5734	χ^2 (14) = 11.79	.6232
Railroad Revitalization and Regulatory Reform Act	1976	12	4	12	F(48,156.1) = .76	.8687	F(48,612) = 1.01	.4663	χ^2 (48) = 48.25	.4629	χ^2 (48) = 48.34	.4591	χ^2 (4[illegible]) = [illegible].75	.7254
OSHA Cotton Dust Standards	1976	13	4	54	F(52,153.2) = .94	.5949	F(52,663) = 1.32*	.0693	χ^2 (52) = 68.72*	.0600	χ^2 (52) = 64.28	.1180	χ^2 (52) = 52.72	.4461
Bank and S & L Deregulation	1978	35	1	1	F(35,22) = .51[a]	.9621	F(35,1960) = 1.31	.1082	χ^2 (35) = 45.74	.1057	χ^2 (35) = 35.82	.4298	χ^2 (35) = 26.97	.8323
Airline Deregulation Act	1978	8	7	48	F(56,226.1) = 1.14	.2497	F(56,384) = 1.43**	.0292	χ^2 (56) = 80.04**	.0192	χ^2 (56) = 80.43**	.0179	χ^2 (56) = 66.30	.1632

* = significant at the .10 level.

** = significant at the .05 level.

[a] Rao's F is exact since N or q is less than or equal to two. A is the number of dummy variables D_{a} (announcement months) and N is the number of firms in the industry sample. The event period is the number of months from the first announcement month to the last announcement month, inclusive.

Based on table 3 of Binder [1983].

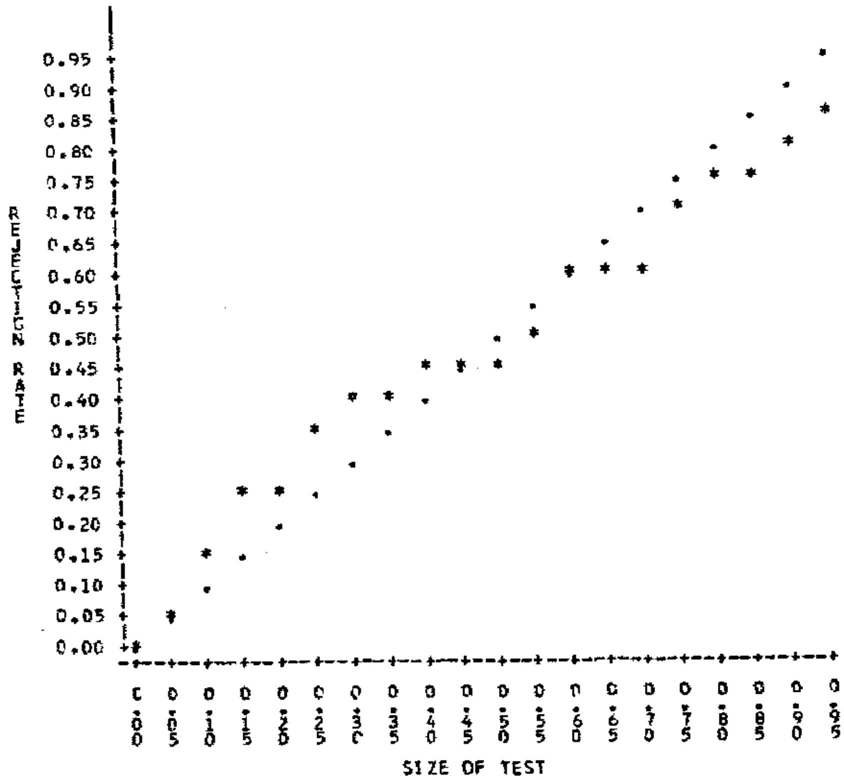

FIG. 1.—Plot of rejection rate versus size of test for Rao's F test in table 2.

The LR test in figure 4 rejects slightly more often than the F and Wald tests and much more than Rao's F. The bias is noticeable when the number of equations is small, e.g., less than five, and it increases as N becomes large. The rejection rates for the LM test are in figure 5. The LM test rejects only slightly more often than Rao's F test. In this case the bias also appears to increase with N. These results indicate that even with a seemingly large ($T = 60$) number of observations the empirical distributions of the asymptotic statistics do not conform to their assumed distributions.[14]

The number of observations can be increased, while still remaining

[14] The distributions of the five statistics reported in table 2 are derived under the assumption that the disturbances in each equation of (3) are normally distributed. If the disturbances are not normally distributed, the absolute values and rejection rates of the statistics would be affected but the relative values and rejection rates would not be. This issue appears to be of minor importance, however, since empirical evidence, e.g., Fama [1976, chap. 4], supports the normality assumption.

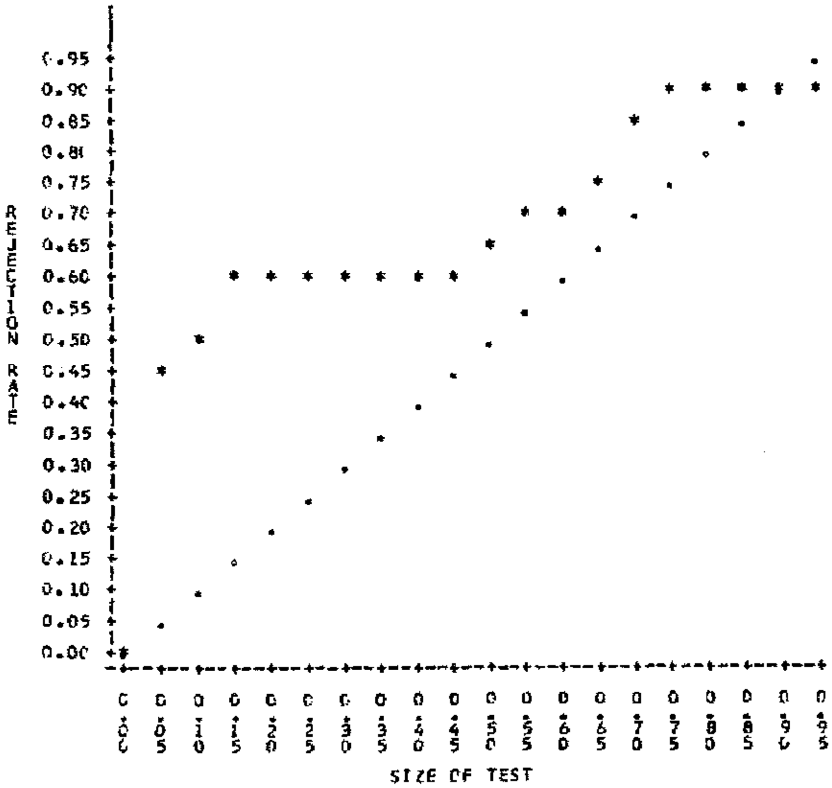

FIG. 2.—Plot of rejection rate versus size of test for the F test in table 2.

within a five-year period, by using daily or weekly returns.[15] Daily returns are frequently used for events after July 1962, which corresponds to the month the *CRSP* daily returns file began. The return equations are usually estimated with approximately 250 daily (one-year) or weekly (five-year) returns. The small sample behavior of the various test statistics under these conditions can be examined by extending the results in table 6 of Binder [1983]. There, I estimated the *MVRM* with 250 daily returns for 13 regulatory changes passed after July 1962 and tested $H3$ for the most important announcement of each with Rao's F statistic.[16] The results of applying the various test statistics to these events are shown in table 3.

The results are similar to those in table 2 except that the degree of bias is greatly reduced by using more observations. The F and Wald statistics confirm closely to the assumed distributions when there are

[15] Most event studies assume that the return-generating process is stationary for a five-year period.

[16] See Binder [1983, p. 44] for a description of the explanatory variables in this system.

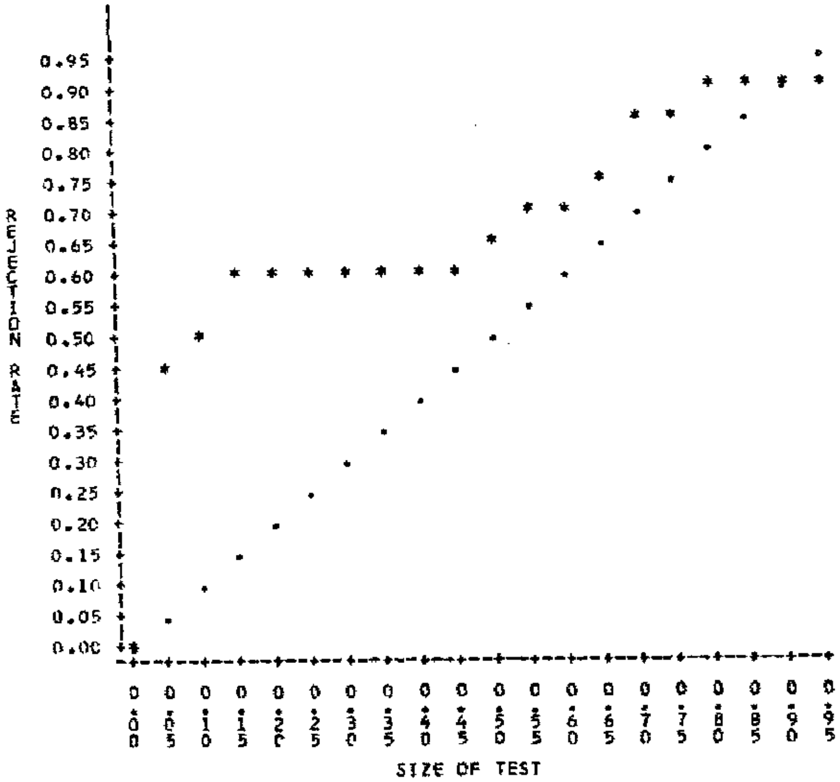

FIG. 3.—Plot of rejection rate versus size of test for the Wald test in table 2.

less than 15 equations, but not when N is 15 or more. For example, when there are 19 equations (the Water Quality Act of 1965) Rao's F test has a p-value of .4102, whereas the F and Wald test p-values are .3119. The bias again increases with the number of equations. The results for the *LR* test parallel those obtained with the Wald and F statistics since the p-values are similar. The p-values for the *LM* test are close to those from Rao's F test, but the *LM* test is still slightly biased against the null hypothesis. The bias seems to increase with the number of equations, although the relation is not as discernible as in table 2. Thus, the choice of test statistic remains important even when daily or weekly data are used, particularly if there are a large number of securities in the sample. Indeed, N is likely to be larger in tests with daily or weekly data than with monthly data since the daily *CRSP* file includes AMEX as well as NYSE stocks, and more stocks are listed in the period after 1962.

5. *Summary*

In this note, I point out the advantages of the *MVRM* methodology in event studies as well as some of its potential problems. The advantage of

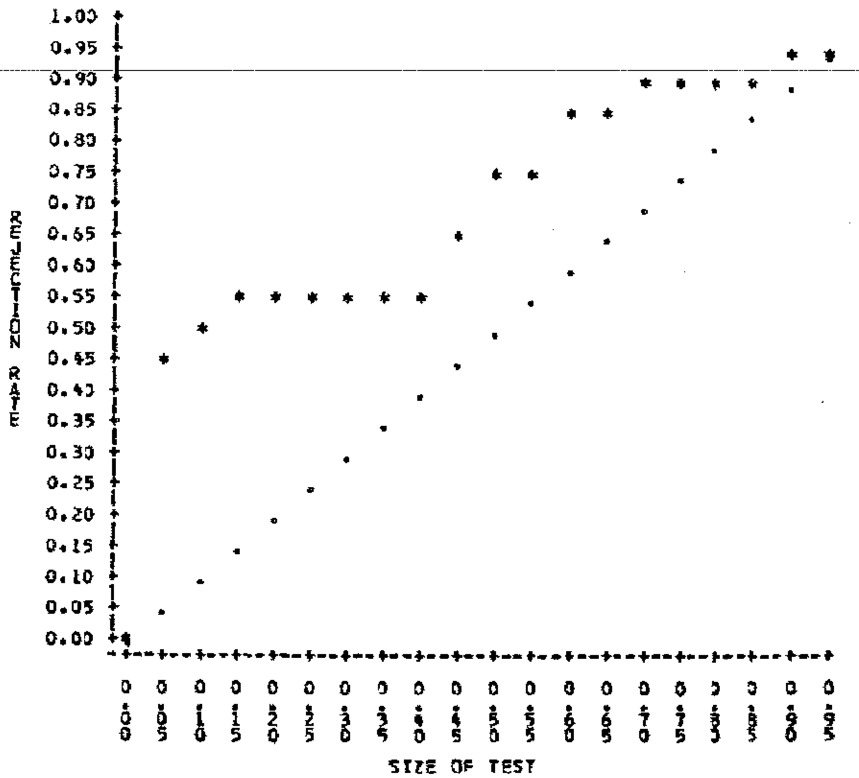

FIG. 4.—Plot of rejection rate versus size of test for the *LR* test in table 2.

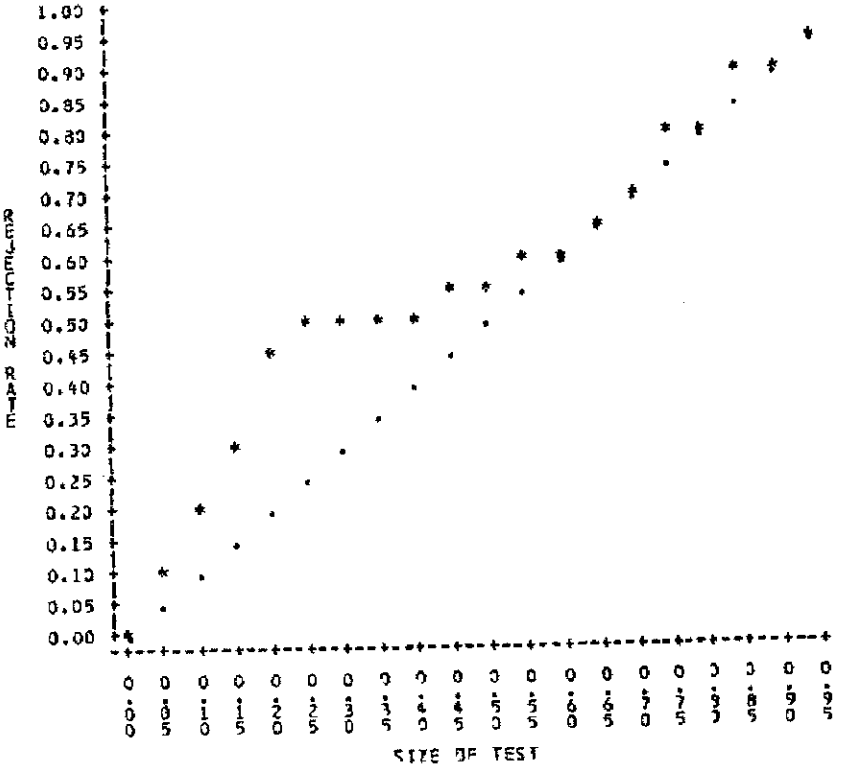

FIG. 5.—Plot of rejection rate versus size of test for the *LM* test in table. 2.

TABLE 3

Tests with Daily Returns of the Hypothesis H3 That All Excess Returns Equal Zero in the Most Important Announcement Period

Regulatory Change	Year	N	A	Event Period	Rao's F Test[a]		F Test		Wald Test		LR Test		LM Test	
					Statistic	p	Statistic	p	Statistic	p	Statistic	p	Statistic	p
Drug Amendments	1962	8	3	33	$F(8,237) = 1.92^*$	.0572	$F(8,1952) = 1.98^{**}$	.0453	$\chi^2(8) = 15.85^{**}$	.0446	$\chi^2(8) = 15.73^{**}$	.0464	$\chi^2(8) = 15.25^*$	.0546
Water Quality Act	1965	19	5	10	$F(19,224) = 1.05$	.4102	$F(19,4958) = 1.13$	.3119	$\chi^2(19) = 21.46$	.3119	$\chi^2(19) = 21.24$	.3237	$\chi^2(19) = 20.36$	.3732
Interest Rate Control Act	1966	3	1	3	$F(3,244) = .27$	.8455	$F(3,738) = .28$	.8399	$\chi^2(3) = .83$	.8423	$\chi^2(3) = .84$	.8399	$\chi^2(3) = .84$	.8398
National Traffic and Motor Vehicle Safety Act	1966	5	2	21	$F(5,241) = .75$	.5859	$F(5,1225) = .77$	.5714	$\chi^2(5) = 3.83$	.5741	$\chi^2(5) = 3.88$	.5668	$\chi^2(5) = 3.85$	.5712
Coal Mine Health and Safety Act	1969	3	2	16	$F(3,243) = .49$	.6908	$F(3,735) = .50$	.6824	$\chi^2(3) = 1.50$	.6823	$\chi^2(3) = 1.52$	.6777	$\chi^2(3) = 1.52$	.6777
Rail Passenger Service Act	1970	14	3	24	$F(14,231) = .87$	.5947	$F(14,3416) = .92$	.5361	$\chi^2(14) = 12.83$	.5400	$\chi^2(14) = 12.81$	.5415	$\chi^2(14) = 12.49$	.5670
Clean Air Act Amendments	1970	5	4	13	$F(5,238) = 1.47$	.2001	$F(5,1210) = 1.49$	.1902	$\chi^2(5) = 7.46$	.1886	$\chi^2(5) = 7.59$	.1803	$\chi^2(5) = 7.48$	.1873
Federal Water Pollution Control Act Amendments	1972	15	3	10	$F(15,230) = 1.27$	.2198	$F(15,3660) = 1.35$	.1633	$\chi^2(15) = 20.26$	.1622	$\chi^2(15) = 19.94$	.1742	$\chi^2(15) = 19.17$	.2061
Bank and S & L Deregulation	1973	12	1	1	$F(12,235) = 1.56$	.1036	$F(12,2952) = 1.60^*$	.0845	$\chi^2(12) = 19.62^*$	.0746	$\chi^2(12) = 19.18^*$	.0843	$\chi^2(12) = 18.46$	.1024
Brokerage Deregulation	1975	2	1	19	$F(2,245) = .19$	.8271	$F(2,492) = .19$	.8270	$\chi^2(2) = .38$	.8270	$\chi^2(2) = .39$	.8228	$\chi^2(2) = .39$	.8228
Railroad Revitalization and Regulatory Reform Act	1976	11	1	12	$F(11,236) = 2.32^{**}$	.0103	$F(11,2706) = 2.42^{**}$	.0054	$\chi^2(11) = 26.67^{**}$	.0053	$\chi^2(11) = 25.64^{**}$	.0073	$\chi^2(11) = 24.37^{**}$	.0113
Bank and S & L Deregulation	1978	31	1	1	$F(31,216) = 1.81^{**}$	.0080	$F(31,7626) = 2.06^{**}$	.0005	$\chi^2(31) = 63.94^{**}$	.0005	$\chi^2(31) = 57.76^{**}$	.0025	$\chi^2(31) = 51.56^{**}$	.0116
Airline Deregulation	1978	7	5	8	$F(7,236) = 1.15$	.3310	$F(7,1694) = 1.18$	.3109	$\chi^2(7) = 8.27$	.3094	$\chi^2(7) = 8.40$	.2986	$\chi^2(7) = 8.26$	.3102

* = significant at the .10 level.

** = significant at the .05 level.

[a] Rao's F test is exact since q, the number of restrictions tested per equation, equals one. A is the number of dummy variables D_{at} (announcement periods) and N is the number of firms in the industry sample. The event period is the number of months from the first announcement month to the last announcement month, inclusive.

Based on table 6 of Binder [1983].

the methodology is that it can test joint hypotheses, which are of greatest importance in studies of regulatory change, the area where this technique has most often been used. The major caveat concerns the choice of test statistic. Several test statistics are shown to be biased against the null hypothesis even when 60 or 250 time-series observations are used. Fortunately, statistics whose small sample distributions are known to a highly accurate approximation, and in some cases exactly known, can be used to test joint hypotheses.

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